Exploring Eye Gaze Visualization Techniques for Identifying Distracted Students in Educational VR

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Abstract

Virtual Reality (VR) headsets with embedded eye trackers are appearing as consumer devices (e.g. HTC Vive Eye, FOVE). These devices could be used in VR-based education (e.g., a virtual lab, a virtual field trip) in which a live teacher guides a group of students. The eye tracking could enable better insights into students' activities and behavior patterns. For real-time insight, a teacher's VR environment can display student eye gaze. These visualizations would help identify students who are confused/distracted, and the teacher could better guide them to focus on important objects. We present six gaze visualization techniques for a VR-embedded teacher's view, and we present a user study to compare these techniques. The results suggest that a short particle trail representing eye trajectory is promising. In contrast, 3D heatmaps (an adaptation of traditional 2D heatmaps) for visualizing gaze over a short time span are problematic.

Index Terms: Human-centered computing—Visualization techniques; Human-centered computing—Visualization design and evaluation methods; Human-centered computing—Usability Testing

1 Introduction

Virtual classrooms are one of the newest aspects of education, allowing students to learn and experience interesting topics from all over the world right from the classroom of their school. Virtual reality has long been suggested as a way to enhance education [53]. Students can virtually take field trips to any place or learn about different machinery and how it works with reduced concern about safety and cost. VR can produce experiences that are vividly remembered, along with numerous other effects that seem to hinge on immersive or embodied experiences [4]. However, there are distractions in VR that may shift a student's focus away from the main educational information [6]. For example, a student may be looking at an object that is not important for the educational content being presented.

VR headsets with eye tracking could be useful for live-guided VR in which a teacher guides a group of students (e.g., a virtual lab, a virtual field trip). Eye-gaze visualizations could help a teacher identify confused/distracted students and then the teacher could adjust explanations or better guide those students towards the objects of interest. Additionally, automated handling of distraction could allow a VR system to vary environment responses to students [24], or the system could display guiding cues to the student [52].

This work explores real-time gaze visualizations for a teacher who is guiding or monitoring students from within VR. The visualizations would be a basis for identifying students who need additional help to direct or maintain attention, helping the teacher understand student attention and improving the effectiveness of educational VR.

Researchers have used line charts, bar charts, coordinate plots and scatter plots to visualize gaze data [10, 44]. However, due to their two dimensional nature, these conventional visualizations are not ideal visualizations for a VR environment. We explored techniques that may be more suitable for gaze-data visualization in a VR environment. In this paper, we present six gaze data visualization techniques and results of a within-subjects experiment to evaluate the effectiveness of these techniques for detecting distracted students. We examined both performance data (response time, and accuracy), and self-reported data on users' impression of these techniques.

2 Related Work

Eye tracking has a wide range of applications [15] such as medical (e.g. eye surgery [33]) and business (e.g. analysis of shopping trends). The eyes have been studied for many decades [2, 13, 42, 50]. Yarbus [51] laid the foundation for this field, analyzing how the eyes work and reporting various findings regarding saccades - the jumps our eyes make when scanning our environment - and fixations - the smoother behavior of our eyes as they focus on a certain object. Recently, eye tracking has been studied for applications in human-computer interaction (HCI), including helping persons with disabilities [19], understanding gaze patterns in various environments [11, 25], as additional input for video games [21], and general HCI use [14, 22, 23].

Embedded eye tracking for VR headsets has rapidly advanced in recent years, enabling increased exploration of interaction techniques using natural eye movements. For example, Piumsomboon et al. [40] recently explored eye-gaze-based selection techniques in VR and found techniques to improve user experience. Pfeuffer et al. [39] explored the combination of eye-gaze and hand-pinch gestures for interaction in VR for a variety of tasks including 3D manipulation, scene navigation, and image zooming. Patney et al. [37] used headset-based eye tracking to explore prioritizing rendering of a scene according to user gaze. Older examples of headset-based eye tracking also exist. For example, Duchowski et al. [16] used eye gaze and fixation identification to observe how participants inspected a VR scene of an aircraft cargo bay.

Eye tracking has been studied to explore user behavior patterns in the educational domain. Slykhuis et al. [43] explored how students attend to science-related photographs and Tsai et al. [48] studied students' visual attention while solving an image-based multiple-choice problems. Eye tracking can also help assess a user's behavior in exploratory learning environments, and the collected data can be used to improve the student model [9]. Eye tracking has also been used to study user attention and engagement. D'Mello et al. [12] used eye tracking to study student engagement in an intelligent tutoring system. Their system used gaze patterns to identify the engagement level of a student and to re-engage students by directing their attention towards an animated tutoring agent. Khokhar et al. [24] proposed an architecture to make a VR pedagogical agent that responds (e.g. pause/replay the VR presentation) to shifts in user

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attention monitored by eye tracking. Yoshimura et al. [52] proposed visual cues to direct student attention in case they shift their focus away from the critical objects in the VR educational environment.

Educational research using VR [29, 32, 36] shows that VR leads to a higher sense of presence and kept the users engaged with the educational content. However, VR could lead to less learning than a video-based presentation [29] possibly due to higher cognitive load. A VR environment is 360 degrees and it has a higher cognitive load than a video on a monitor screen. We believe that by monitoring students' attention, a teacher could better assist students if they get distracted. Our gaze data visualization techniques could be very helpful for monitoring students in a VR based classroom.

Visualization researchers studied several techniques that laid a foundation for gaze-data visualization. Borgo et. al [5] surveyed guidelines and implementation techniques of Glyphs, a small independent visual object that depicts attributes of a data record. Glyphs [8, 27] have been used to represent multiple data attributes through visual channels, such as position, size (length, area, and volume), shape, color, angle, orientation, curvature, and dynamics (motion speed and direction). Meghdadi et al. [31] used a space-time cube showing moving objects over a map along with a timeline as a part of its trajectory visualization. Colors have been popularly used in visualization [45, 47] to differentiate between different elements while presenting information. We use different colors to show gaze data from multiple students in an educational VR environment.

Researchers have used various techniques for visualizing gaze data including line charts, bar charts, coordinate plots and scatter plots to visualize gaze data [1, 10, 34, 44]. Some used a virtual element such as a circle or dot to indicate the gaze direction [1, 34]. A continuous trace starting from the viewer to the object of interest has also been used [35, 46]. Zhang et al. [54] used a long pointed arrow to indicate gaze direction of multiple users in a collaborative work environment. Thanyadit et al. [46] proposed the use of an augmented reality (AR) device to visualize students' position and gaze direction in a VR environment. They used a graph drawing algorithm to reduce visual clutter due to many visual cues for multiple students in a VR environment. A common technique for investigating visual attention is the aggregation and representation of gaze target positions in a superimposed attentional map known as a heatmap [17, 30]. A heatmap can show areas gazed for more time by a user. Kurzhals et al. [26] analyzed eye gaze data for dynamic stimuli, such as video or animated graphics, to identify trends in the general viewing behavior. Their technique aggregated information from multiple users to generate an attention map that is somewhat similar to a heatmap. Pfeiffer et al. [38] designed a 3D attention volume to visualize the 3D point of regard for a given user. Rahman et al. [41] explored gaze data visualizations for VR but no formal user study was conducted. Blascheck et al. [3] proposed a taxonomy of eye-tracking visualization and classified techniques into two categories: point-based and area-of-interest-based methods. Most of the techniques we stud here were point-based except for a heatmap-style cue (Section 3).

Most prior eye tracking data visualization techniques were developed for desktop or mobile views. As part of our work, we adapted prior techniques to now visualize eye gaze directly in VR.

3 Gaze Visualization Techniques

We introduce six visualization techniques to represent eye gaze in VR: 1) Gaze Ring, 2) Gaze Disk, 3) Gaze Arrow, 4) Gaze Trail, 5) Gaze Trail with Arrows, and 6) Gaze Heatmap. Similar to past research [1, 34, 54], the first three techniques only consider the current gaze point. At each gaze point, a visual indicator is displayed slightly in front of the gazed-at object (from the viewer's perspective) and faces the viewer. This helps ensure a clear view of the indicator by avoiding interpentration into the scene object. Our last three techniques display a gaze data history as well as the current gaze point. Such techniques have been used in the past [3, 17, 30, 31, 38] for visualizing data over a timespan. All these techniques work for multiple users (students in our case) and each user is represented with a unique and distinct color in the visual cue.

3.1 Gaze Ring (GR)

In this technique, a colored ring appears at the gaze location (see Fig. 1(a)). A ring allows an unobstructed view of the virtual environment with minimal distractions in front of the object being viewed. The intuition for this technique was that many people draw circles around objects they want to draw attention to. This may make ring indicators easy to understand from a quick glance.

3.2 Gaze Disk (GD)

This technique places indicators similarly to the gaze ring, but a small disc appears instead of a ring (see Fig. 1(b)). The disk size was smaller than the rings to minimize obstruction of the scene.

3.3 Gaze Arrow (GA)

Three dimensional arrows indicate the gaze, with the arrow tip at the current gaze point. Arrows are commonly used to indicate the location of objects of interest. Thus, we thought that these will be intuitive and suitable to indicate the current gaze point of a user. In our environment, arrows are 3 meters long and pointed-to objects are roughly 30 meters from the viewer, leading to the appearance seen in Figure 1(c).

3.4 Gaze Trail (GT)

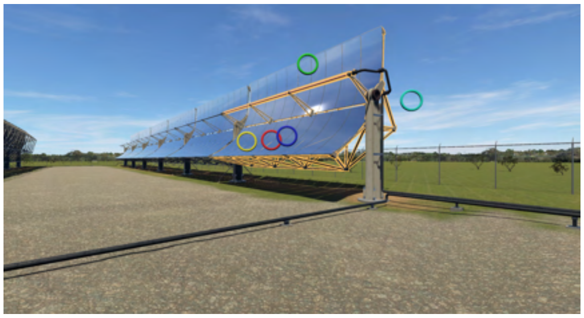
This technique represents a gaze history, i.e., gaze trails are an aggregation of gaze points over a time span (see Fig. 1(d)). Such visualizations have been used in the past [31] for visualizing trajectories. We implemented the trail with a particle system in which the particle emitter moves to each new gaze point, with a particle lifetime of three seconds. Thus, it represents a 3-second gaze trail. New particles (recent gaze points) look brighter than older particles.

3.5 Gaze Trail with Arrows (GTA)

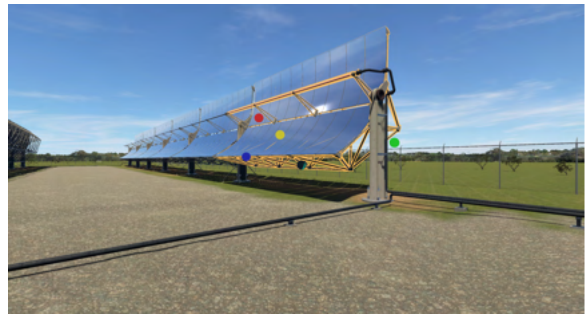
This technique appears somewhat similar to gaze trail, but this trail is rendered using static line segments (instead of particles) and arrows appear along the trail indicating the gaze movement direction (see Fig. 1(e)). Line segments are added between gaze points subject to a minimum length requirement (no segment is added between very close gaze points). One arrow is rendered per three line segments. The oldest segments are removed as new ones are added. A small sphere is added at the front of the trail to emphasize the current gaze. The idea behind this technique is a non-fading history which should make it easier to detect if a student was distracted recently. For subject material where a particular order of observation is required for comprehension, this technique can be resourceful.

3.6 Gaze Heatmap (GH)

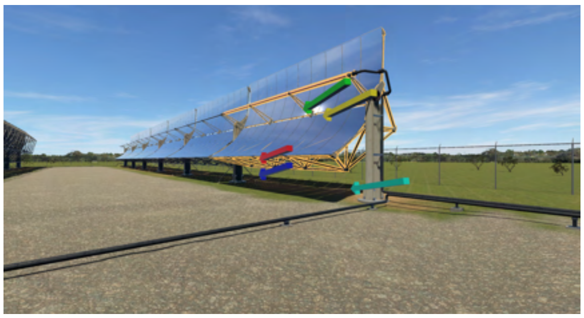
The idea for this technique came from two-dimensional heat maps [17] in which gaze points aggregate to create an image with colors representing the aggregated density. Typically, the color red is associated with areas of more visual attention, corresponding to more gaze points near a given location. Heatmaps have been explored in the past [30] for visualizing gaze data for a single user. We adapted the technique to three dimensions and to a multi-user environment. Students' gaze location is rendered directly on the objects using a custom shader (see Fig. 1(f)). Each student is given a different base color that overlays the object's color around gaze points, with opacity and saturation varying with density of nearby gaze and age of gaze points. Colors from different students combine additively when they overlap. The heatmap "cools" quickly (3 seconds) to emphasize recent (dis)attention and to show the same amount of history as other techniques (GT and GTA).



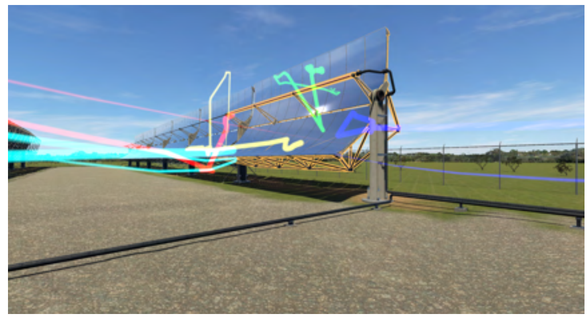
(a) Gaze Ring: a ring appears at the gaze location.



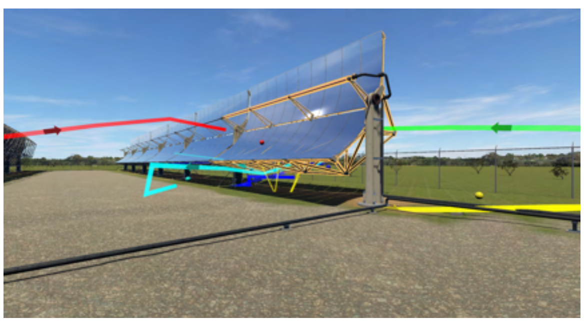
(b) Gaze Disc: a disc appears at the gaze location.



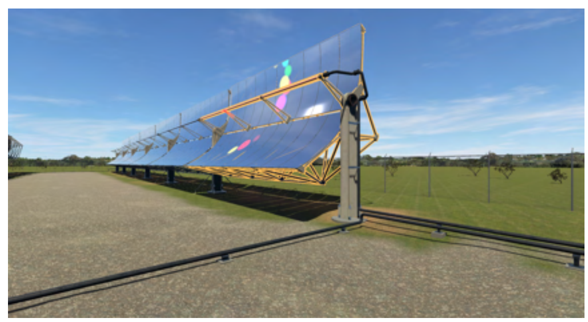
(c) Gaze Arrow: an arrow indicates the current gaze point.



(d) Gaze Trail: a trail of particles is shown for each user based on his/her gaze points over the last three seconds.



(e) Gaze Trail with Arrows: line segments with arrows represent gaze point movement.



(f) Gaze Heatmaps: change the color of the object being gazed at.

Figure 1: Eye gaze visualization techniques shown from a teacher's point of view.

4 User Evaluations

We conducted a within-subjects usability experiment with the six visualization techniques to evaluate their effectiveness for detecting student distraction. We considered both single-student and 5-student VR settings. We had 2 independent variables: technique type (TT) (6 choices) and student mode (SM) (1 student or 5 students in the scene). Thus, in total, we had $6 \times 2 = 12$ conditions for each user and there was only one trial for each condition. Each trial took about 2-4 minutes. Our dependent variables were mean response time and mean accuracy, where the mean is taken over a given condition for a given user. For each condition (trial), there would be multiple distraction events and each of those will have a response time and accuracy (if the user was correct) associated with it. Additionally, we asked the participants to rank the techniques based on their preference for both single and multiple student cases. Based on previous findings in related work and our impression of these techniques, we had the following hypotheses:

Hypothesis 1 (H1): Visualization techniques with a history of gaze points would have a slower response time than the techniques that show only the current gaze point.

Hypothesis 2 (H2): The accuracy of detecting a distracted student would be higher in the case of a single student.

Hypothesis 3 (H3): People will prefer a technique that shows history since history makes it easier to track a student's gaze.

4.1 Participants and Apparatus

We recruited 26 participants (18 male and 8 female, age from 18 to 57 years, and mean age 25.1) from the university population. 20 participants had prior experience with a VR device. The experiment duration ranged from 45 minutes to 60 minutes. The experiment setup (Figure 2) included a 27" Dell monitor, a HTC Vive Pro with

Figure 2: Experimental Setup.

a Vive controller, and a PC (Core i7 8700K, GTX 1080 Graphics card, 16 GB RAM) with Microsoft Windows 10. We used Unity 3D v2017.4.30f1 software for implementing VR techniques.

A HTC Vive Pro Eye was used to pre-record student gaze data for playback during experiment trials. None of the participants from these recording were allowed to participate in the main study. We used a VR solar field for this educational experience wherein a teacher overviewed solar plant components [7]. A student was supposed to follow the pre-recorded teacher's audio instructions and look at four different objects while we recorded gaze. The currently selected object was highlighted to help the students understand where they were supposed to look, and the teacher described the highlighted objects to maintain attention. Every object had its own audio cue that played when highlighted. Every student experienced the same objects, in randomized order. In total, we obtained 6 different data sets with similar distraction levels where each set had 6 recordings: one for a single student and five for the multiple student case. Sets were composed from individual recordings in such a way that sets had similar average distraction levels to each other, but distraction varied within each multi-student group. Each eye gaze recording had a duration of about 2 minutes and each had a maximum of 4 (average 2) distractions. Per main experiment trial, a data set was randomly selected for playback.

4.2 Experiment Design and Procedure

The participants were assigned the role of a teacher's assistant helping the prerecorded teacher keep track of distracted students. The participants experienced the same VR point of view as the teacher did when the teacher was recorded. This allowed participants to approximate a teacher role, without having to learn to teach the material, and in a controlled manner with prerecorded sessions.

The experiment began with the participant seated at the station (Figure 2) and the moderator seated to the side. Participants were seated in front of the monitor at a distance of about 3-4 feet with a Vive controller in their dominant hand to indicate student distractions. Participants were given a standard consent form that explained the study. They were then given a pre-questionnaire that collected their general information (age and gender) and asked a few questions (see Table 1) from the immersive tendencies questionnaire [49].

Each subject went through a training phase to get used to the VR environment and get a clear idea of the study procedure. This training scene especially helped participants who had no prior experience using VR. It required them to practice using the controller to report distractions. The training phase used a scene different from the actual trial and none of the six techniques tested were presented. The training phase used an experimental gaze visualization from earlier prototypes (showing both student position and gaze direction) and an audio cue explaining the study process. Participants were tasked with detecting distracted students in each trial. Participants were instructed to handle simultaneous distractions (where multiple students are distracted at the same time) as one event. For reporting distractions, participants were asked to press the trigger button as soon as any student gets distracted and release the button when no one is distracted. A progress bar also appears on the screen which indicates the pressure on the trigger button when pressed. The training phase lasted for about 5 minutes for each participant. They were instructed that if a student looks away only briefly (about a second) and then looks back at the object of interest then s/he would not be considered distracted.

The real trials followed the training phase. Participants were presented with the techniques in random order (Latin-square design [18]). First, we presented the scene with a single student for each technique, followed by the 5-student version for each technique in the same order as the single student case. The system randomly selected and highlighted one of the four objects from the scene and a corresponding teacher's audio cue was played. The system logged a distraction event whenever a pre-recorded student looked away from the selected object for more than a second. For each trial, we recorded the response time and correctness (accuracy) for detecting each distraction. The response time was defined as the time from when the distraction began to the time when the participant pressed the trigger button. The accuracy was defined as the percentage of times the participant was correct about distractions i.e., when there was a distraction and they detected it (indicated by trigger press). Both false positives and false negatives were considered as an error in detecting distraction. After each trial, a questionnaire (see Table 2) appeared in the virtual environment and they indicated their answers to the moderator to complete an online Google form for recording responses. Then they ranked the techniques based on their preference, from most favorite to the least favorite, for both single and multiple student cases. For the ranking task, to avoid any confusion with technique names, they were allowed to revisit the techniques to refresh their memory about each technique.

5 Results

Mean ratings for the immersive tendencies questions (see Table 1) are summarized in Figure 3. We noticed that:

- Almost all of our participants reported being mentally alert.
- Most participants reported getting immersed in an activity.
- The majority of participants reported having the ability to block distractions while performing an activity.
- Most participants reported being frequent video game users.

Performance data were analyzed with repeated-measures 2-factor ANOVA, per dependent variable, and post-hoc analysis with pairwise sample t-tests. We used Holm's sequential Bonferroni adjustment

Table 1: Immersive Tendencies Questionnaire. Participants answered these questions as 7 point Likert-like items.

Immersive Tendencies Questions	
Q1	How mentally alert do you feel at the present time?
Q2	Do you ever become so involved in an activity like reading a book or a TV program or a game that you forget about your surroundings ?
Q3	How good are you at blocking out external distractions when you are involved in something?
Q4	How often do you play video games?

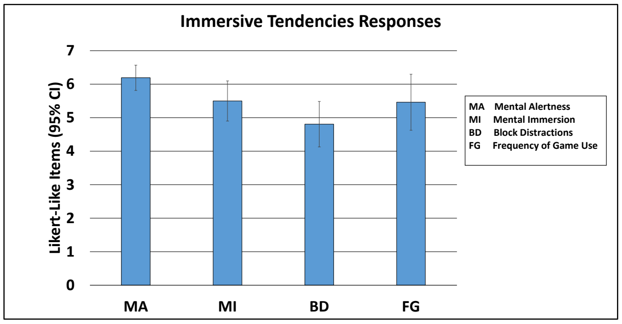


Figure 3: Mean ratings for the immersive tendencies questions.

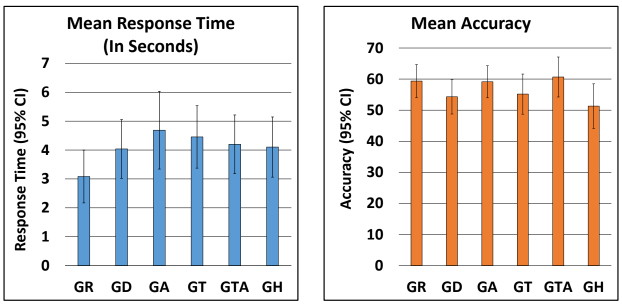


Figure 4: Mean response time in seconds and accuracy.

to correct for type I errors [20] and the Shapiro-Wilk test to make sure the data was parametric. To analyze Likert-like items, we used Friedman's test with post-hoc analysis using Wilcoxon Signed-Rank test. To determine significance, we used $\alpha = 0.05$.

Repeated measures 2-factor ANOVA results are shown in Table 3. Mean response time and accuracy for all the techniques are summarized in Figure 4. We did not find any significant difference in response time based on technique type or student mode (single vs. multiple). However, overall accuracy was significantly different based on student mode. The accuracy was significantly higher for the multiple student case vs. the single student case for all the techniques on an average (see Figure 5). The t-values of the pairwise tests are summarized in Table 4. All techniques showed better accuracy in the case of multiple students.

Mean ratings for post-questionnaire questions 1 to 3 (see Table 2) for single student and multiple student cases are summarized in Figure 6 and Figure 7 respectively. The results of Friedman's test for comparing the techniques, for questions 1 to 3 of the post-questionnaire, are summarized in Table 5. There was no significant difference in terms of Q1 (overall distraction level of students) for

Table 2: Post-Questionnaire. Participants answered questions 1-3 as 7 point Likert-like items. Q4 was an open ended question.

Post-Questionnaire Questions	
Q1	What was the overall distraction level of the student(s)?
Q2	How well did the visual cue help you understand where the students were looking?
Q3	How easy was it to detect a distracted student with this visual cue?
Q4	What is good about this technique? What is bad about this technique

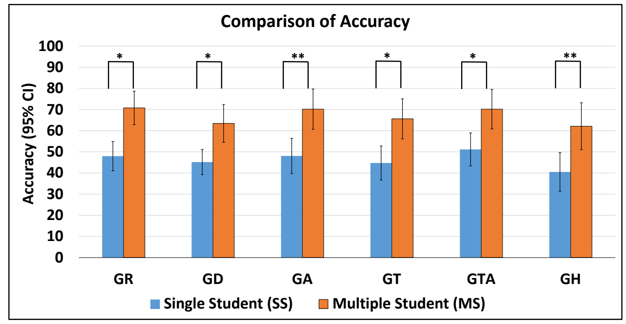


Figure 5: Accuracy comparison between single student and multiple student cases (* = $p < 0.005$, ** = $p < 0.01$).

both single student and multiple student cases. However, there was a significant difference for Q2 (easy to find look direction) and Q3 (ease of distraction detection). A summary of results for pairwise Wilcoxon Signed-Rank test for post-questionnaire questions is shown in Table 6 for the single student case and in Table 7 for the multiple student case. Based on these results, we observe:

- In both student conditions, participants found that it was significantly more difficult to find where a user is looking (Q2) and detect a distracted student (Q3) with the GH technique compared to the GR, GD, GT, and GTA techniques.
- In single student cases, participants found that it was significantly more difficult to find where a student is looking (Q2) and detect a distracted student (Q3) with the GA technique compared to the GT and the GTA techniques.
- In single student cases, participants found that it was significantly more difficult to detect a distracted student (Q3) with the GA technique compared to the GR technique.

Our ranking counts for Rank 1 (Figure 8) suggest that the Gaze Trail (GT) was the most strongly liked technique followed by the Gaze Ring (GR) and the Gaze Disk (GD) technique. Gaze Arrow (GA) and the heatmap (GH) do not look promising. Further analysis can consider the distribution of ranks across different techniques as shown in Figure 9 and Figure 10. In both single-student and 5-student cases, Gaze Arrow (GA) and Gaze Heatmap (GH) received

Table 3: Repeated measures 2-factor ANOVA results. TT: Technique Type used and SM is student mode (single or multiple)

Source	Response Time	Accuracy
TT	$F_{5,20} = 0.818, p = 0.551$	$F_{5,21} = 1.205, p = 0.341$
SM	$F_{1,24} = 0.342, p = 0.564$	$F_{1,25,} = 37.262, p < 0.005$
TT×SM	$F_{5,20} = 1.071, p = 0.406$	$F_{5,21} = 0.074, p = 0.996$

Table 4: Summary of pairwise t-tests for comparing accuracy between single student and multiple student case for each technique

Technique	Accuracy t-values
GR	$t_{25} = -4.287, p < 0.005$
GD	$t_{25} = -3.475, p < 0.005$
GA	$t_{25} = -2.964, p < 0.01$
GT	$t_{25} = -3.430, p < 0.005$
GTA	$t_{25} = -3.269, p < 0.005$
GH	$t_{25} = -2.95, p < 0.01$

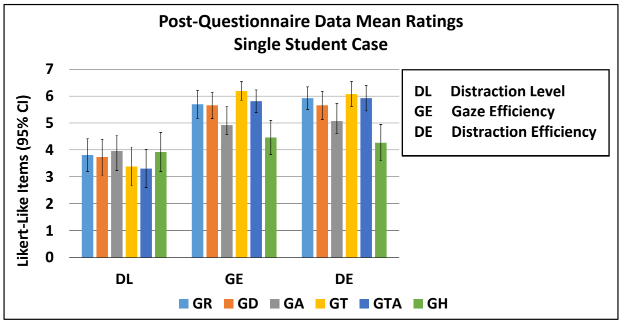


Figure 6: Mean ratings for the post-questionnaire questions 1 to 3 in case of a single student. Q1: DL, Q2: GE and Q3: DE.

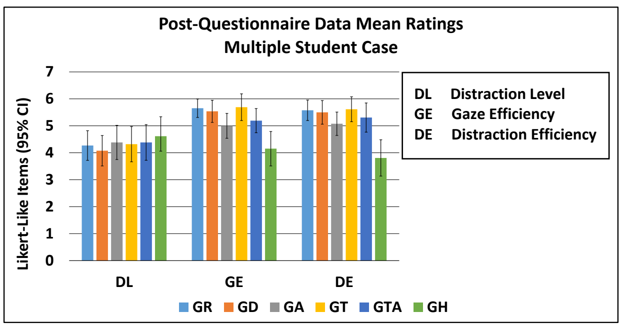


Figure 7: Mean ratings for the post-questionnaire questions 1 to 3 in case of multiple students. Q1: DL, Q2: GE and Q3: DE.

a substantial number of lowest-rank scores (Rank 6). Gaze Ring (GR) and Gaze Disc (GD) are mostly ranked above the middle value (3.5), but with fewer Rank 1 scores than GT.

Friedman's test indicated a significant difference between ranks of different techniques for both single student ($\chi^2 = 23.01, p < 0.005$) and multiple student cases ($\chi^2 = 19.407, p < 0.005$). A summary of results for pairwise Wilcoxon Signed-Rank tests is shown in Table 8 for both single student and multiple student cases.

We asked the participants if they had any comments or suggestions about the techniques. Our participants did not like the Gaze Arrow (GA) technique since the size and the orientation of the arrow did not feel intuitive enough, although one subject mentioned the larger body helped when there were multiple students. The Gaze Trail (GT) was the most preferred technique and some users suggested a shorter fade time for the particle trail. Some participants mentioned the trails helped them retrace a student's data in case the participants had lost track of a student in a multiple student scenario. The Gaze Arrow (GA) had almost similar comments but with the addition that the arrow in the techniques could be a different color to make it more visible. The Gaze Heatmap (GH) in general was hard to keep track of and the visualization of the technique appeared

Table 5: Summary of Results for Friedman's test for post-questionnaire questions 1 to 3

Questions	Single Student	Multiple Student
Q1 (DL)	$\chi^2 = 4.328, p = 0.503$	$\chi^2 = 3.005, p = 0.699$
Q2 (GE)	$\chi^2 = 29.148, p < 0.005$	$\chi^2 = 18.623, p < 0.005$
Q3 (DE)	$\chi^2 = 27.741 p < 0.005$	$\chi^2 = 27.841, p < 0.005$

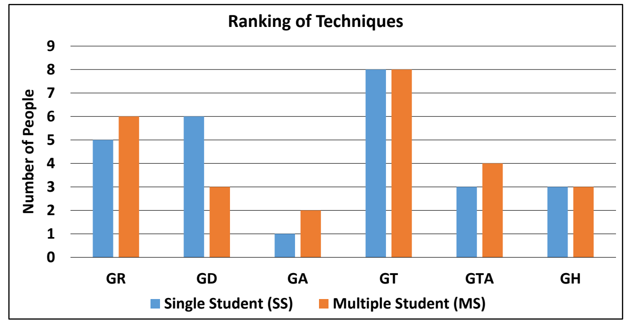


Figure 8: Ranking summary. This plot shows the number of people who picked each technique as their most favorite (Rank 1).

rushed (due to a short fade time of 3 seconds). This was the only technique that changed the color of the virtual objects in the scene, instead of an additional 3D object/trail appearing in the scene. A few participants (4 to be exact) suggested that the colors for different students should adapt to the environment such that they are very different from the colors of objects in the scene. This would differentiate the heatmap technique from the scene objects and would improve the effectiveness of this technique.

6 Discussion

Our results suggest that the response time was roughly similar for all the techniques irrespective of the number of students present in the scene. We did not find any statistically significant difference in response times for the techniques. All the techniques were presented to the participants for a short duration (2-3 minutes per trial). Possibly, if the users spend more time with these techniques, we should be able to reduce the variability in trial-mean response time. We were unable to accept our hypothesis H1.

Surprisingly, we found that the accuracy of detecting distracted students was significantly higher for the multiple student case. We thought that it would be easier to detect a distraction if there was only one student. However, it turned out that most of our participants made more errors in the case of a single student, thereby reducing the accuracy. One possible reason is that they tried the single student case before the multiple student case. Thus, they could have learned to use these techniques better for the multiple student case, even though there was a training phase. Another possibility is that, in the case of multiple students, there were more gaze representations to be tracked by the participant and a distraction could come from any of those students, causing participants to press the trigger button more often than in the single student case. In practice, we could address the first possibility with longer training and by randomizing the single/multiple student cases such that all single/multiple student cases are not grouped together (as in case of our experiment). Based on this result, we were unable to accept our hypothesis H2.

Our ranking data shows that the Gaze Trail (GT) was most often given the top rank, followed by Gaze Ring (GR) and Gaze Disk (GD). However, participants may moderately reduce ranking of Gaze Disk (GD) for multiple students because they found the disks difficult to track in the virtual environment. Other history-based techniques (GTA and GH) appear less preferred by participants. Based on this information, we were unable to accept hypothesis H3. However, it is possible that showing a history contributes to the success of GT even though history is not sufficient for other techniques to be as strongly liked. Followup work could tune the length of the history (particle life) to learn more about its effects.

In the past, a heatmap [17, 30] has mainly been used to identify areas that grabbed more attention of users of a 2D environment.

Table 6: Summary of results of pairwise Wilcoxon Signed-Rank test for post-questionnaire questions 1 to 3 for single student case.

Pairs	Q1 (DL)	Q2 (GE)	Q3 (DE)
GR×GD	$Z = -0.061, p = 0.951$	$Z = -0.185, p = 0.853$	$Z = -0.709, p = 0.478$
GR×GA	$Z = -0.511, p = 0.609$	$Z = -1.891, p = 0.059$	$Z = -2.977, p < 0.005$
GR×GT	$Z = -0.914, p = 0.361$	$Z = -1.877, p = 0.060$	$Z = -0.882, p = 0.378$
GR×GTA	$Z = -1.124, p = 0.261$	$Z = -0.334, p = 0.739$	$Z = -0.087, p = 0.931$
GR×GH	$Z = -0.246, p = 0.806$	**$Z = -3.318, p < 0.005$**	**$Z = -3.348, p < 0.005$**
GD×GA	$Z = -0.615, p = 0.538$	$Z = -1.764, p = 0.078$	$Z = -1.450, p = 0.147$
GD×GT	$Z = -0.648, p = 0.517$	**$Z = -1.996, p < 0.05$**	$Z = -1.025, p = 0.305$
GD×GTA	$Z = -0.849, p = 0.396$	$Z = -0.409, p = 0.683$	$Z = -0.789, p = 0.430$
GD×GH	$Z = -0.419, p = 0.676$	**$Z = -3.382, p < 0.005$**	**$Z = -3.008, p < 0.005$**
GA×GT	$Z = -1.262, p = 0.207$	**$Z = -2.836, p < 0.05$**	**$Z = -2.773, p < 0.05$**
GA×GTA	$Z = -1.695, p = 0.090$	**$Z = -2.058, p < 0.05$**	**$Z = -2.068, p < 0.05$**
GA×GH	$Z = -0.164, p = 0.870$	$Z = -0.808, p = 0.419$	$Z = -1.703, p = 0.089$
GT×GTA	$Z = -0.022, p = 0.982$	$Z = -1.637, p = 0.102$	$Z = -0.652, p = 0.514$
GT×GH	$Z = -0.943, p = 0.346$	**$Z = -3.988, p < 0.005$**	**$Z = -3.531, p < 0.005$**
GTA×GH	$Z = -1.112, p = 0.266$	**$Z = -2.932, p < 0.005$**	**$Z = -2.938, p < 0.005$**

Table 7: Summary of results of pairwise Wilcoxon Signed-Rank test for post-questionnaire questions 1 to 3 for multiple student cases.

Pairs	Q1 (DL)	Q2 (GE)	Q3 (DE)
GR×GD	$Z = -0.495, p = 0.621$	$Z = -0.619, p = 0.536$	$Z = -0.266, p = 0.790$
GR×GA	$Z = -0.446, p = 0.656$	**$Z = -2.347, p < 0.05$**	**$Z = -1.998, p < 0.05$**
GR×GT	$Z = -0.155, p = 0.877$	$Z = -0.302, p = 0.762$	$Z = -0.052, p = 0.958$
GR×GTA	$Z = -0.562, p = 0.574$	$Z = -1.237, p = 0.216$	$Z = -0.583, p = 0.560$
GR×GH	$Z = -1.005, p = 0.315$	**$Z = -3.428, p < 0.005$**	**$Z = -3.569, p < 0.005$**
GD×GA	$Z = -0.939, p = 0.348$	$Z = -1.784, p = 0.074$	$Z = -1.834, p = 0.067$
GD×GT	$Z = -0.506, p = 0.613$	$Z = -0.563, p = 0.574$	$Z = -0.225, p = 0.822$
GD×GTA	$Z = -0.860, p = 0.390$	$Z = -1.120, p = 263$	$Z = -0.231, p = 0.817$
GD×GH	$Z = -1.902, p = 0.072$	**$Z = -2.858, p < 0.005$**	**$Z = -3.253, p < 0.005$**
GA×GT	$Z = -0.102, p = 0.919$	$Z = -1.717, p = 0.086$	$Z = -1.304, p = 0.192$
GA×GTA	$Z = -0.143, p = 0.886$	$Z = -0.824, p = 0.410$	$Z = -0.643, p = 0.520$
GA×GH	$Z = -0.763, p = 0.446$	**$Z = -2.173, p < 0.05$**	**$Z = -2.903, p < 0.005$**
GT×GTA	$Z = -0.164, p = 0.870$	$Z = -1.774, p = 0.076$	$Z = -1.360, p = 0.174$
GT×GH	$Z = -0.997, p = 0.319$	**$Z = -3.226, p < 0.005$**	**$Z = -3.653, p < 0.005$**
GTA×GH	$Z = -0.432, p = 0.666$	**$Z = -2.440, p < 0.05$**	**$Z = -2.733, p < 0.05$**

Table 8: Summary of results of pairwise Wilcoxon Signed-Rank test for the ranking data

Pairs	Single Student	Multiple Student
GR×GD	$Z = -0.159, p = 0.874$	$Z = -0.662, p = 0.508$
GR×GA	**$Z = -3.163, p < 0.005$**	**$Z = -3.113, p < 0.005$**
GR×GT	$Z = -0.333, p = 0.739$	$Z = -0.423, p = 0.673$
GR×GTA	$Z = -1.453, p = 0.146$	$Z = -1.318, p = 0.188$
GR×GH	$Z = -2.749, p = 0.006$	**$Z = -2.951, p < 0.005$**
GD×GA	**$Z = -2.793, p < 0.005$**	$Z = -2.427, p = 0.015$
GD×GT	$Z = -0.077, p = 0.939$	$Z = -0.039, p = 0.969$
GD×GTA	$Z = -0.1.348, p = 0.178$	$Z = -0.657, p = 0.511$
GD×GH	**$Z = -2.853, p < 0.005$**	$Z = -2.667, p = 0.008$
GA×GT	$Z = -2.650, p = 0.008$	$Z = -1.843, p = 0.065$
GA×GTA	$Z = -2.196, p = 0.028$	$Z = -1.654, p = 0.098$
GA×GH	$Z = -0.141, p = 0.888$	$Z = -0.679, p = 0.497$
GT×GTA	$Z = -1.283, p = 0.200$	$Z = -0.920, p = 0.358$
GT×GH	**$Z = -2.855, p < 0.005$**	$Z = -2.718, p = 0.007$
GTA×GH	$Z = -1.740, p = 0.082$	$Z = -2.088, p = 0.037$

We adapted the technique for 3D VR and real-time gaze viewing, showing three seconds of history as with our other history-based

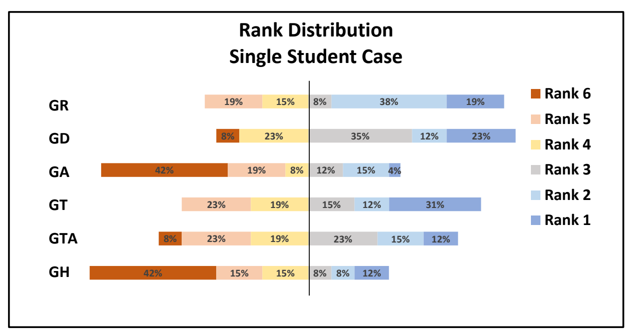


Figure 9: Distribution of ranks for each technique in case of a single student (divergent stacked bar graph with bars horizontally positioned according to a middle rank value of 3.5).

techniques. This resulted in a "fast-cooling" heat map resembling a gaze trail drawn directly on object surfaces. Our pilot testing suggested that this short-term effect was better for emphasizing gaze movements than conventional heat maps in which long-term aggregation focuses on longer time scales. The GH heat map may

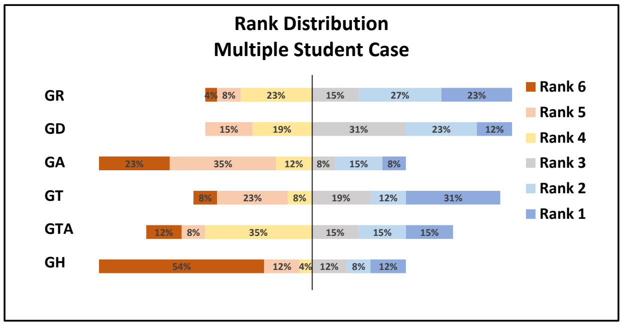


Figure 10: Distribution of ranks for each technique in case of multiple students (divergent stacked bar graph with bars horizontally positioned according to a middle rank value of 3.5).

have been more difficult to follow than other techniques like GT because of visual gaps in the updating point when gaze moves away from an object during distraction. The heat map cannot be rendered in mid air, so it appears to hop to the next object or to a different depth (e.g., the distant ground) in a discontinuous manner. In contrast, GT draws a continuous path across gaps. Our results indicate that heatmap-based visualizations on 3D objects are not suitable for live visualization of short-term gaze information. The technique may work better in certain types of environments, such as objects on a desk, where gaps or jumps in depth are minimized. Possibly, using a low pass filter could make the heatmap a little better since it would avoid sudden jumps in the gaze location leading to fewer jumps in depth.

Student privacy is an important concern when sharing eye-gaze data of students with the teacher. In our study, all eye-tracking data was collected from adults who gave permission to use their data within a standard informed consent model, and without recording any information that could be used to fully de-anonymize it later. However, given that demographic information may be discerned from gaze data [28], great caution must be taken when handling it, especially if it has been gathered from minors (school students). If such a VR-based system is used for a real classroom, one must ensure that students understand the meaning of eye tracking (perhaps by having them review example visualizations) and get permission from the students (and their parents, for minors) to track or record their eye gaze. Special care has to be taken for any longer-term storage to provide security, address legal requirements, and avoid any misuse of gaze data.

There are a few limitations that could have affected our results. We did not find statistically significant performance differences between visualization techniques (response time, accuracy). It may be that there is no substantial performance difference between these visual techniques, and then the choice of cue would be guided by the subjective measures. Limited experiment power should also be considered. Individual trials were not very long and this limited distraction events. Missing one event resulted in a considerable reduction in accuracy. Distractions recorded from students, rather than simulated, cannot be precisely controlled or classified, increasing variability. We sorted recordings into sets of similar average distraction and used an objective gaze angle test to classify distraction. Sometimes, the participants could see that students were not looking at the relevant object but they decided students should get some leeway before being identified as distracted. The subject's judgment of distraction level could also limit the consistency of responses. An extended experiment could use longer trials and more subjects to increase experiment power, and could treat distraction level as a variable for analysis. There were accuracy differences detected between single-student and multi-student cases. Comparing between these two cases was not, however, the main goal. All of our participants first tried the experiment with a single student and that could contribute to improved accuracy for the multi-student case. Finally, the participants for this study, playing the role of a teacher's assistant, were mostly undergraduate students. Their results could differ from experienced teachers, limiting immediate applicability to real VR classrooms. Nonetheless, we expect that our results are useful for various applications and users, because they provide a basic step towards understanding user experiences when monitoring eye gaze directly in VR. Clarity and appeal of visual cues is a core aspect that may transfer between users or applications.

7 Conclusion and Future Work

We proposed six gaze-data visualization techniques for an educational VR environment to help detect distracted students. These visualizations would help identify students who are confused/distracted, and the teacher could better guide them to focus on the object of interest in the VR environment. We conducted an in-depth study comparing the techniques proposed. A within-subjects experiment was conducted that examined performance data (in terms of response times and accuracy in detecting distracted students) and data on user perception of these techniques. We considered two cases in terms of VR class size (Single student vs. Multiple student). Our results show that, although there was no significant difference for response time between techniques, participants performed better in case of multiple students for all the techniques. The Gaze Trail (GT), a short particle trail, was the technique most frequently given the top rank by participants. In contrast, the study revealed problems of applying heat maps on 3D objects surfaces for real-time gaze visualization.

We considered only gaze-based distractions for this experiment. However, attention cannot be determined solely based on eye gaze data since there are many other factors involved (like physical and mental well being) which could affect the attention level. A student could be looking at the object of interest and still be distracted mentally. Thus, for future work, we would like to include more sensing (such as heart rate, skin conductance, EEG, etc.) as part of our student distraction detection system. We would also like to explore how these techniques behave as the number of students increases (say 20, or 50) in the virtual class. For a large class, we think that filtering out and only showing the data for distracted students in combination with an algorithms to reduce visual clutter [46] would help. We used recorded gaze data of students for this experiment. In the future, it would also be interesting to see the performance of these techniques (for detecting distracted students) for a class with real students.

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